Prediction of Ventricular Tachycardia by a Neural Network using Parameters of Heart Rate Variability

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Abstract

In this paper, we propose a classifier that can predict ventricular tachycardia (VT) events using artificial neural networks (ANNs) trained with parameters from heart rate variability (HRV) analysis. The Spontaneous Ventricular Tachyarrhythmia Database (Medtronic Version 1.0), comprising 106 pre-VT records and 126 control data, was used. Each data set was subjected to preprocessing and parameter extraction. After correcting the ectopic beats, data in the 5 minute window prior to the 10 second duration of each event was cropped for parameter extraction. Extraction of the time domain and non-linear parameters was performed subsequently. Two-thirds of the database of extracted parameters was used to train the ANN, and the remainder was used to verify the performance. ANNs for classifying the VT events was developed, and the sensitivities of the ANN was 82.9% (71.4% specificity). The normalized area under the receiver operating characteristic (ROC) curve of the ANN was 0.75.

1. Introduction

About 80% cases of sudden cardiac death (SCD) are caused by spontaneous ventricular tachyarrhythmia (VTA) [1], which means that the prediction of both ventricular tachycardia (VT) and ventricular fibrillation (VF) will surely contribute to increasing the survival rate of patients with heart problems. Numerous methods have been reported previously for predicting VTAs [2]. Among these methods, predictions based on heart rate variability (HRV) analysis have recently emerged [3].

This paper proposes a predictor for VT based on an ANN that is trained using multiple parameters from HRV analysis methods. Initially, eleven parameters from time domain, frequency domain, and nonlinear analysis are calculated [4,5] from short-term recordings (5 minutes) prior to the VT events and control data. After calculating the parameters, an ANN classifier was trained using two-thirds of the parameter database. Finally, performance of the trained ANN as a predictor for VT was tested on the remaining one-third of the database.

2. Methods

2.1. Database

RR interval time series were obtained from the PhysioNet's Spontaneous Ventricular Tachyarrhythmia Database Version 1.0 from Medtronic, Inc. (http://physionet.org/physiobank/database/mvtdb/). The database was collected from records of 78 patients with ICDs (63 male and 15 female, aged 20.7 to 75.3) and consisted of the following RR intervals: 106 pre-VT records and 126 control data sets. Each series included 1024 RR intervals prior to the corresponding event. Short-term HRV analysis was performed on the RR intervals in 5 minute window located 10 seconds apart from the each event. Figure 1(a) shows an example of the RR interval tachogram prior to a VT episode.

2.2. Preprocessing and parameter extraction

Prior to parameter extraction, ectopic beats were corrected to reduce errors especially in the frequency domain analysis. A method that utilized the heart timing signal based on the integrated pulse frequency modulation model [6] was applied to handle the ectopic beats in the original database. Figure 1(b) shows the RR interval tachogram after ectopic beat correction. After correcting ectopic beats, four time domain parameters (MeanNN, SDNN, RMSSD, and pNN50) and three nonlinear parameters of Poincaré plot (SD1, SD2, and SD1/SD2) were calculated within the 5 minute window as shown in figure 1(b).

Frequency domain parameters were extracted by detrending the RR interval tachograms using a time-varying finite-impulse response high-pass filter followed by resampling at 7 Hz after subjecting to a cubic spline interpolation. Figure 1(c) shows the tachogram of a windowed region in figure 1(b) after detrending and interpolation. The power spectral density (PSD) of the

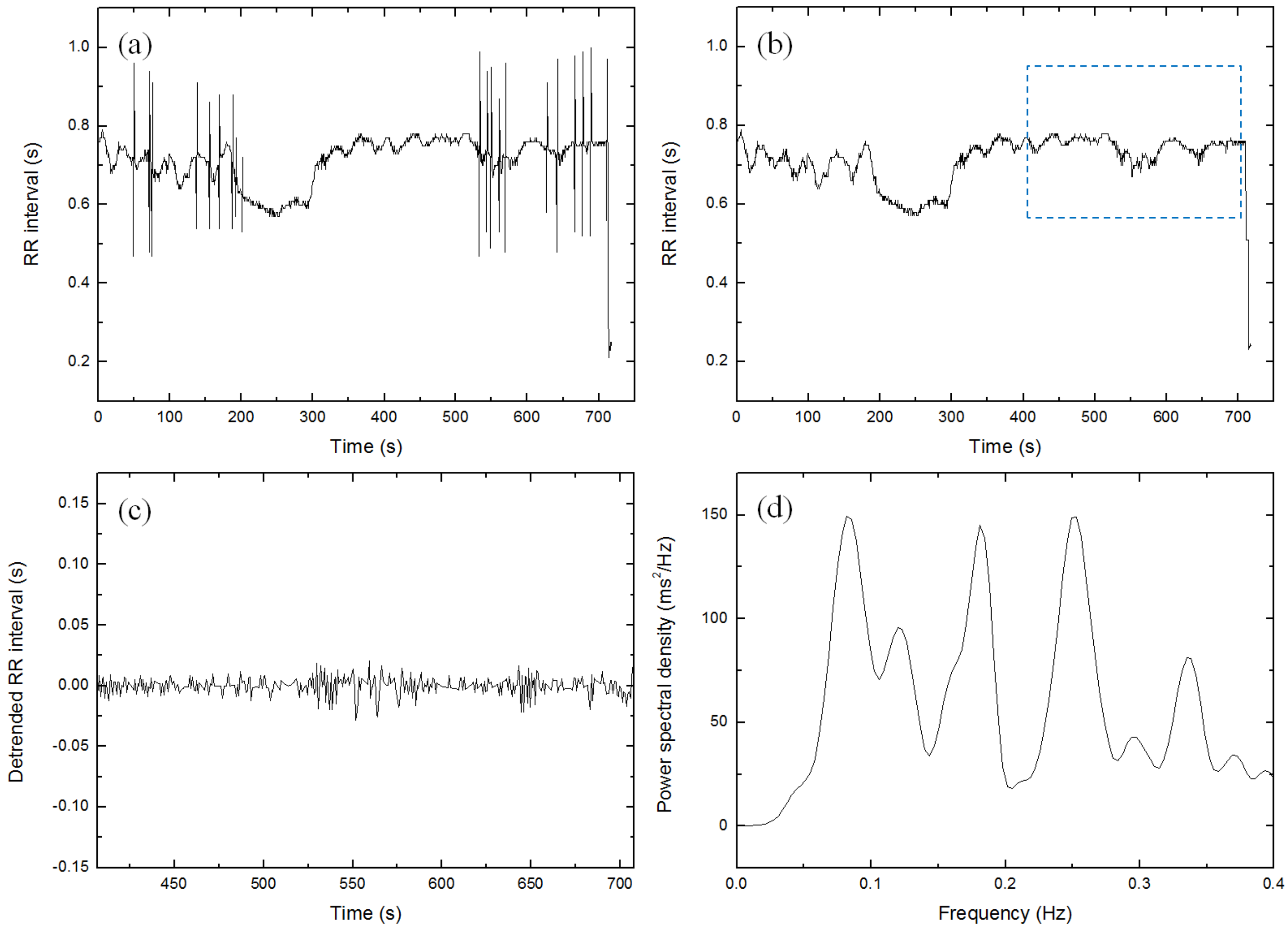

Figure 1. (a) An original RR interval tachogram of a pre-VT record and (b) the tachogram after the ectopic beat correction of (a). The dashed window indicates a selected region, 5 minute in length, used for short-term HRV parameter extraction. (c) The RR interval tachogram of the windowed region in (b) after subjecting the curve to detrending, interpolation, and resampling. (d) Power spectral density of (c) computed using Welch's periodogram.

resampled data was computed using Welch's periodogram with a 512-point Hann window with 50% overlap. The spectral powers in the VLF, LF, and HF regions were then calculated. Figure 1(d) shows the PSD of the tachogram shown in figure 1(c).

A detailed description of the eleven parameters used in this study is provided in table 1.

2.3. ANN training

Within the extracted parameter database, randomly selected two-thirds of the data was used to train an ANN for classifying VT events. The training set therefore included extracted parameters from 71 pre-VT and 84 control data. Meanwhile, the remaining one-third of the data (35 pre-VT and 42 control data) was set aside for evaluating the performance of the trained ANN.

A general multilayer perceptron neural network structure and back propagation learning rule was used to train the ANN. For the training of an ANN, a value of +1 was given as the target of the output for the inputs of VT events, and –1 was given as the target of the control input. Training was stopped when the mean square error fell below 10^{-5}. Finally, the network topology of the ANN was determined experimentally.

3. Results

In classifiying the VT episodes, an ANN with a topology having 11 input nodes, 25 neurons in the first hidden layer, 30 neurons in the second hidden layer, and one output node showed the best performance. With the cutoff set to the half the output scale (0), the trained ANN showed 100% accuracy for the training set and 76.6% (59/77) accuracy for the test set. Specifically, the sensitivity, specificity, and positive predictive value (PPV) were 82.9% (29/35), 71.4% (30/42), and 70.7% (29/41), respectively. Figure 2 indicates the receiver

Table 1. Detailed description of parameters used in this study.

Methods	Parameters	Units	Description
Time domain analysis	MeanNN	ms	Mean of NN intervals
	SDNN	ms	Standard deviation of NN intervals
	RMSSD	ms	Square root of the mean squared differences of successive NN intervals
	pNN50	%	Proportion of interval differences of successive NN intervals greater than 50 ms
Frequency domain analysis	VLF	ms^2	Power in very low frequency range (0 – 0.04 Hz)
	LF	ms^2	Power in low frequency range (0.04 – 0.15 Hz)
	HF	ms^2	Power in high frequency range (0.15 – 0.4 Hz)
	LF/HF		Ratio of LF over HF
Nonlinear analysis	SD1	ms	Standard deviation of the successive intervals scaled by $1/\sqrt{2}$ $\sqrt{\frac{1}{2}\mathrm{Var}(\mathrm{RR}_n - \mathrm{RR}_{n+1})}$
	SD2	ms	$\sqrt{2\mathrm{SDNN}^2 - \frac{1}{2}\mathrm{SD1}^2}$
	SD1/SD2		Ratio of SD1 over SD2

operating characteristic (ROC) curve of the ANN for VT events computed by sweeping the cutoff value within the full scale of the output (–1 to +1), the normalized area under the curve (Az) of which was 0.75.

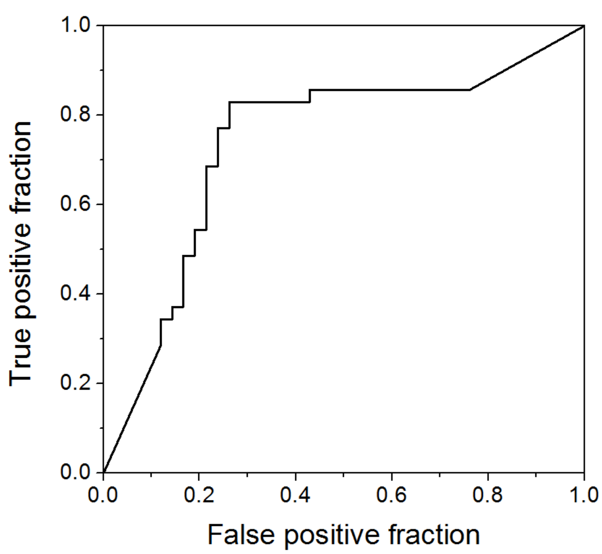

Figure 2. ROC curve for the ANN trained for VT prediction.

4. Discussion

We proposed a classifier for pre-VT events by utilizing ANNs trained with parameters from the short-term analysis of HRV. The accuracies of classifying VT events were 76.6% and the Az value was 0.74. The classification result was not outstanding, but the ANN showed good performance in distinguishing pre-VT events from the control. Furthermore, the parameters used in this study were not specially developed or calculated, but were used widely for general short-term HRV analysis, which indicated that the classifiers developed could be easily applied to general devices used in HRV analysis. In addition, by implying the developed prediction algorithm for VT into general ICDs, patient monitors or personal health monitoring devices, considerable reduction in the mortality from SCD could be achieved due to pre-warning of VT events.

ANNs require significant calculation, thus, devices with high computational power are necessary to implement the developed classifiers. This may be a serious drawback for adoption of the developed method. However, by running the classifiers at 30 seconds or one minute intervals, power consumption can be greatly reduced. In addition, with the development of modern integrated circuit technology, high performance processors operating with very low power requirements have been introduced and are now commercially available. This feature will facilitate the adoption of the developed algorithms for ICDs and portable or wearable devices for ubiquitous healthcare. Furthermore, further research on the optimization of the developed algorithm will reduce the burden of this high computational necessity.

The database that was used in this study has a relatively small number of records (232 records in total). Therefore, the results presented may suffer from a lack of statistical sampling. Another limitation is the length of the RR interval records in the database. Each record only includes RR intervals of 1024 beats prior to specific events due to the storage limitations of the ICDs. The short recording time prevented making use of long-term data prior to VT events. In addition, the database was collected from patients with ICDs of a single manufacturer. The performance of devices may vary if data from ICDs made by a different company are used.

5. Conclusions

In this study, we made predictors of VT by training ANN with parameters of HRV analysis. An ANN classifier trained with parameters from short-term HRV analysis was developed and the efficacy of the classifier was verified using data collected from ICDs in this study. The trained ANN performed well in classifying VT events although the sample number was insufficient to ensure statistical satisfaction. The performance of the proposed classifiers should be further investigated using additional data collected in different environments.

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